Properties of Gamma-Ray Burst Classes

Jon Hakkila*, David J. Haglin*, Richard J. Roiger*, Robert S. Mallozzi†, Geoffrey N. Pendleton†, & Charles A. Meegan‡

*Minnesota State University, Mankato, Minnesota 56001
†University of Alabama, Huntsville, Alabama 35812
‡NASA/MSFC, Huntsville, Alabama 35812

Abstract. The three gamma-ray burst (GRB) classes identified by statistical clustering analysis [7] are examined using the pattern recognition algorithm C4.5 [8]. Although the statistical existence of Class 3 (intermediate duration, intermediate fluence, soft) is supported, the properties of this class do not need to arise from a distinct source population. Class 3 properties can easily be produced from Class 1 (long, high fluence, intermediate hardness) by a combination of measurement error, hardness/intensity correlation, and a newly-identified BATSE bias (the fluence duration bias). Class 2 (short, low fluence, hard) does not appear to be related to Class 1.

INTRODUCTION

GRB spectral and temporal properties overlap, providing a continuum of burst characteristics. Some of this overlap is intrinsic in nature, while much is due to instrumental and observational biases. In addition to this overlap, there is clustering indicative of classes within the parameter space defined by GRB attributes. In particular, there are two long-recognized GRB classes [2,5] based on duration (divided at roughly 2 seconds) and spectral hardness. A statistically significant third class has been identified using statistical clustering analysis [7].

Can effects attributable to a source population be separated from instrumental effects? To answer this, we have applied computer science pattern recognition algorithms to learn why bursts cluster in some parameter spaces. For this analysis, we have used the supervised decision tree classifier C4.5 [8]. Supervised classifiers establish rules for previously identified patterns, and must be trained by representative class members.

ANALYSIS

The three GRB classes identified by statistical clustering techniques [7] can be found from three significant classification attributes; 50 to 300 keV fluence, T90 duration, and HR321 hardness ratio (the fluence in the 100 to 300 keV band divided by the fluence in the 25 to 100 keV band). The properties of the three classes in terms of these attributes are demonstrated in Table 1.

TABLE 1. Statistical clustering classes, from 3B GRBs.

Attributes	Class 1 (Long)	Class 2 (Short)	Class 3 (Intermediate)
T90:	long	short	intermediate
Fluence:	large	small	intermediate
Hardness:	intermediate	hard	soft

C4.5 was trained on the three GRB classes using five fluences, two durations, three peak fluxes, and three hardness ratios. C4.5 produced a decision tree containing IF THEN ELSE branches for placing each GRB in the appropriate class; these branches were *pruned* to remove branches containing less than four GRBs. Rules were then generated for each class based on the pruned branches. C4.5 identifies outliers with poorly defined rules that often contain few GRBs. Statistical methods find that outliers are not closely bound to the class (cluster) centers. C4.5 rules identified a number of GRBs as having peculiar hardness ratios; these resulted from large individual channel fluence errors. The GRBs with the largest 10% relative errors (error divided by measurement) were subsequently removed from the database. The remaining 3B GRBs were reclassified using C4.5; the resulting rules were used to classify 4B Catalog GRBs and thus increase the database size.

Class 3 Spectral Hardnesses

C4.5 verified that the three GRB classes resulted primarily from the attributes of spectral hardness, duration, and fluence. With the larger classification database, the dependence on spectral hardness could be examined in terms of the spectral fitting parameters α, β, and E_{peak} [1]. Using only these three attributes, C4.5 was able to accurately classify most of the 4B GRBs. The rules generated by C4.5 were able to cleanly separate Class 2 from Class 1, but could not delineate Class 3 from Class 1 (85% of Class 3 bursts were assigned to Class 1).

Upon further examination, Class 3 GRBs were found to have E_{peak} values similar to Class 1 bursts of the same 1024 ms peak flux (Figure 1). The correlation between E_{peak} and peak flux has been interpreted as cosmological redshift [6].

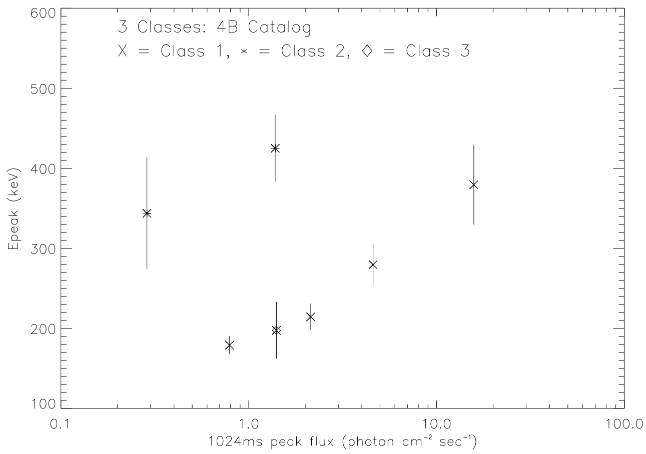

FIGURE 1. E_{peak} vs. p1024 for the Three GRB Classes.

Class 3 Fluences and Durations

Since at least one of the three defining characteristics of Class 3 actually represents a data correlation, we hypothesized that Class 3 GRBs actually belong to Class 1. We decided to see if Class 3 fluences and durations could be explained in terms of Class 1 attributes. This could be the case if some instrumental or sampling bias made Class 1 GRBs appear to be shorter and fainter than they should be.

Figure 2 is a plot of fluence vs. 1024 ms peak flux for each of the three GRB classes, and is limited to GRBs detected when BATSE had one homogeneous set of trigger criteria. There are distinct regions outside of which no GRBs are found. GRBs with 1024 ms peak fluxes less than 0.2 photons cm^{-2} $second^{-1}$ are not detected, since this is below BATSE's minimum detection threshold. GRBs do not have fluences less than what would be found in their time-integrated 1024 ms peak fluxes, since this is the shortest timescale on which this peak flux can be measured.

Figure 3 overlays log(T90) contours for Class 1 GRBs on the fluence vs. 1024 ms peak flux space. The contours demonstrate that GRBs can be modeled as a series of pulses, with pulses containing most of the fluence and interpulse separations primarily defining the duration. Most Class 2 bursts are single-pulsed events as measured on the 1024 ms timescale. This helps define the characteristics of the third distinct region outside of which no GRBs are found: high fluence, faint Class 1 GRBs are missing, whereas low fluence faint, Class 1 GRBs are present. Since a bias favoring detection of GRBs with few photons over those with many photons seems unlikely, we suspect a bias capable of underestimating fluence relative to peak flux.

We have dimmed a number of bright GRBs to where they just trigger in order to study their measured properties as they fade into background. Each

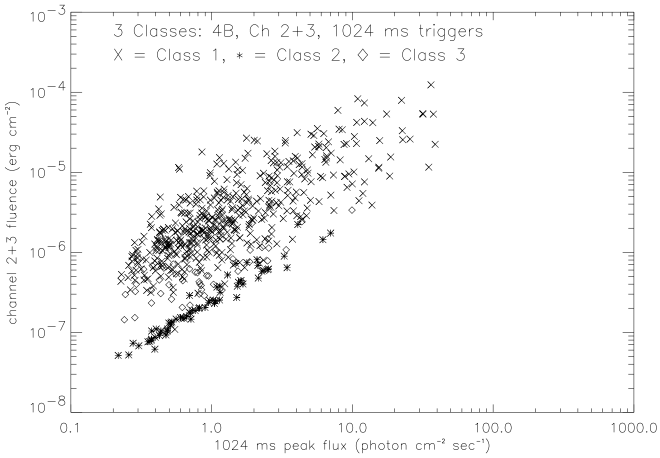

FIGURE 2. Fluence vs. p1024 for the Three GRB Classes.

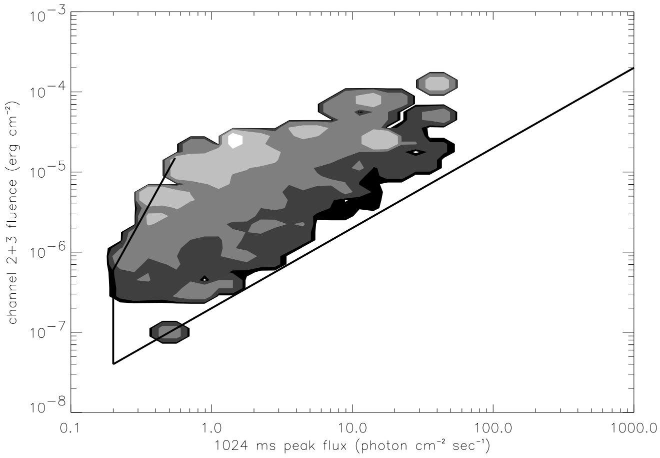

FIGURE 3. Fluence vs. p1024 for Class 1 GRBs; contours indicate regions of constant log(T90).

burst's peak flux is dimmed, and the time history is "noisified" with a Poisson background. The peak flux and fluence are then re-measured. These actions have been performed ten times on five bright bursts with a range of temporal structures.

One problem quickly became apparent during the analysis: the time interval bounding the fluence measurement (the *fluence duration* [4]) strongly influenced the amount of fluence measured. If the same fluence duration interval was used for undimmed and dimmed measurements, then the fluence-to-peak flux ratio did not change as a GRB was dimmed. If, however, the fluence duration interval shortened to account for faint pulses disappearing into the background and becoming unrecognizable, then the fluence-to-peak flux ratio decreased as the burst dimmed (see Figure 4). This bias becomes stronger near the trigger threshold.

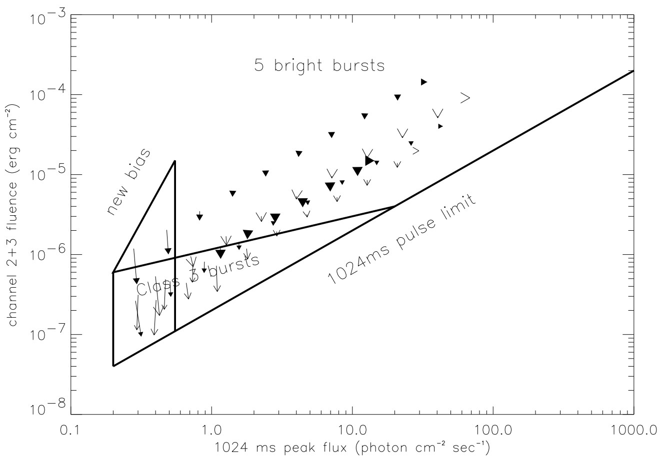

FIGURE 4. Five bright Class 1 GRBs, decremented in peak flux, noisified, with remeasured fluences and peak fluxes. It has been assumed that the GRB duration is measured from identifiable pulses, which become harder to recognize as the peak flux becomes fainter.

Fluence durations taken from BATSE Catalogs provide supportive evidence for this mechanism. The durations used to calculate fluence of faint Class 1 GRBs are shorter than those of bright Class 1 GRBs [4].

CONCLUSIONS

A mechanism exists whereby some Class 1 (Long) GRBs can develop Class 3 (Intermediate) characteristics via a combination of the hardness intensity relation and the fluence duration bias. Faint Class 1 GRBs are most likely to develop Class 3 characteristics, but it is possible for even bright GRBs with appropriate time histories and spectral features to develop these characteristics. Class 3 (Intermediate) GRBs do not therefore appear to represent a separate source population, although they cluster in the duration, fluence, hardness, attribute space. Class 2 (Short) GRBs do appear to represent a separate source population. We were unable to find a mechanism by which faint Class 1 GRBs could develop Class 2 characteristics.

GRB population studies can benefit from use of AI classifiers. There are many other attributes developed by the community that could be included for future study. To this end, we are designing a web-based AI tool for GRB classification [3] that includes supervised and unsupervised AI classifiers [9].

REFERENCES

1. Band, D. L., *et al.*, *ApJ* **413**, 281 (1993).
2. Cline, T. L., and Desai, U. D., *Proc. 9th ESLAB Symp.*, 1974, pp. 37-45.
3. Haglin, D. J., *et al.*, this conference.
4. Hakkila, J., *et al.*, this conference.
5. Kouveliotou, C., *et al.*, *ApJ* **413**, L101 (1993).
6. Mallozzi, R. S., *et al.*, *ApJ* **454**, 597 (1995).
7. Mukherjee, S., *et al.*, *ApJ* **508**, 314 (1998).
8. Quinlan J. R., *Machine Learning* **1**, 81 (1986).
9. Roiger, R. J., *et al.*, this conference.